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Acquisition Management for Systems-of-Systems: Analysis of Alternatives via Computational Exploratory Model

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Acquisition Management for Systems-of-Systems: Analysis of Alternatives via Computational Exploratory Model

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Executive Summary

The Department of Defense (DoD) has placed a growing emphasis on the pursuit of agile capabilities via net-centric operations. The breadth of technological advancements in communication and sensing has generated exciting opportunities for battlefield systems to exploit collaboration to multiple effects. In this setting, systems able to interoperate along several dimensions increase the efficiency of the overall system-of-systems (SoS) manifold. However, the manner in which these SoS are acquired (designed, developed, tested, and fielded) hasn't completely kept pace with the shift in operational doctrine. In our current project, we have attempted to unravel the layers of complexities in an SoS acquisition program, outline an acquisition strategy better suited for such programs, and develop an exploratory analysis tool to provide insights into the acquisition process.

The research efforts during the one year study period have focused on the development and consequent extension of prior frameworks of the Computational Exploratory Model (CEM) —a discrete event simulation model— and its associated analytical representation, the Markov approach, to investigate the impact of development dependencies on the successful acquisition of an SoS. These efforts also include a complementary decision analysis tool that is based on investment portfolio theory. The conceptual model for acquisition strategy proposed in our project is based on the 16 technical management and technical system-engineering processes outlined in the *Defense Acquisition Guidebook (DAG)*, often referred to as the 5000-series guide. Our conceptual model for acquisition is centered on the revised processes of the 2007 System-of-Systems System Engineering (SoS-SE) manual. The Markov-based analytical approach seeks to augment the CEM approach by developing a method that enables the comparison of networks of systems that are interconnected and quantifying the cascading effects

of development risk. The goal of this research work is to allow acquisition professionals to develop intuition for procuring and deploying an SoS. The investment portfolio-based approach pursues this goal by providing a means of objectively choosing baskets of systems that comprise an SoS, which balances performance against developmental cost and risk from resulting system interdependencies.

Applications of the Markov network analysis method and investment portfolio approach enables the identification of optimal SoS network topologies and provides a tool for acquisition professionals to identify the features of an SoS that contribute most to the successful progression (or delays) in the development process.

This report summarizes the progress made during the previous year's work that enhanced the ability to address systems-specific risk, its propagation to interdependent systems, and the comparison of SoS alternatives. This analysis of alternatives is made possible by both the Markov-based model as well as the investment portfolio-based optimization approach developed by the researchers during this period. Example studies presented in this report illustrate both the Markov approach and investment portfolio approach for constructed sample problems. The Markov analytical model is demonstrated for a conceptual coffee maker example (summarized from our published journal article). The investment portfolio-based method is applied to an acquisition scenario for the Littoral Combat Ship (LCS) initiative.

Outreach & Collaboration

Our work during the project period has resulted in one external journal publication, one conference paper/presentation, and one submitted conference paper (for the 2012 NPS Acquisition Symposium).

First and foremost was a journal article submission that was accepted and published in the *ASME Journal of Mechanical Design* (Mane et al., 2011). The article included updated work that extends the Markov perspective to also include time-varying elements of the Markov model. The article and associated research received valuable feedback through the review process and provided additional insight. The feedback included suggestions for transition probability estimations and issues on scalability of the method to larger sized problems. Second, we delivered an earlier conference paper and presentation on the Markov approach at the IEEE System, Man, and Cybernetics (SMC) Conference in Anchorage, AK, in October 2011. Feedback from both journal article reviewers and presentation attendees has enhanced the knowledge base developed for further proliferation of the Markov-based model in this research. Third, we submitted the investment portfolio work for presentation and proceedings publication at the upcoming NPS Acquisition Research Symposium, May 15–17, 2012, in Monterey, CA. We anticipate that the contributed work will warrant further collaboration and additional discourse, particularly with members of the NPS community who conduct research in portfolio methodologies and investment valuation research.

Additionally, we have identified key figures both in the NPS and PEO-LCS communities who we feel are instrumental for collaboration in the ongoing research work. The identified figures include current lead system integrators for the Navy's LCS endeavor and draws potential for further enrichment of the current portfolio example that is based on current LCS efforts. We intend to incorporate an added dimension of realism to the currently developed methods through collaborations with these connections and receiving direct feedback from real-world acquisition practitioners. This will serve as a rich basis for further ideations and the development of the portfolio-based approach into a mature decision-making platform.

Introduction

The purpose of capabilities-based acquisition, as described by Charles and Turner (2004), is to acquire a set of capabilities instead of acquiring a family of threat-based, service-specific systems. The Missile Defense Agency (MDA), for example, uses capability-based acquisition to evaluate the success of a program based on its ability to provide a new capability for a given cost, and not on its ability to meet specific performance requirements (Spacy, 2004). The Joint Mission Capability Package (JMCP) concept is another example that aims to create a joint interdependency between systems to combine capabilities in order to maximize reinforcing effects and minimize vulnerabilities (Durkac, 2005). The goal of the JMCP effort is a more efficient utilization of both human- and machine-based assets and, in turn, improved combat power.

To accomplish the desired capability, systems are increasingly required to interoperate along several dimensions, which characterizes them as SoS (Maier, 1998). SoS most often consist of multiple, heterogeneous, distributed systems that can (and do) operate independently but can also collaborate in networks to achieve a goal. Examples of SoS include civil air transportation (DeLaurentis et al., 2008), battlefield ISR (Butler, 2001), missile defense (GAO, 2007b), etc. According to Maier (1998), the distinctive traits of operational and managerial independence are the keys to making the collaboration work. The network structure behind the collaboration, however, can contribute both negatively and positively to the successful achievement of SoS capabilities and, even earlier, to the developmental success. Collaboration via interdependence may increase capability potentials, but it also contains concealed risk in the development and acquisition phases. Brown and Flowe (2005), for instance, have investigated the implications of the development of SoS to understand the drivers that influence cost, schedule, and performance of SoS efforts. Results of their study indicate that the major drivers—as indicated by subject-matter-experts—include systems standards and requirements, funding, knowledge, skills and ability, system interdependencies, conflict management, information access, and environmental demands.

Disruptions in the development of one system can have unforeseen consequences on the development of others if the network dependencies are not accounted for. The goal of a single system's program manager is the mitigation of risk leading to successful development of that specific system. While program managers nearly always consider direct or immediate consequences of decisions, they often don't consider the cascading second- and third-order effects that result from the complex interdependencies between constituent systems in an SoS. It falls on acquisition managers and systems engineers (or SoS engineers) to understand and manage the successful development of a system, or family of systems, to produce the targeted capability in this challenging setting.

Abundant evidence suggests that SoS-oriented endeavors have struggled to succeed amidst the development complexity. The Future Combat System (FCS) is the most recent example (Gilmore, 2006). Civil programs have not been spared either, for example, the Constellation Program (Committee on Systems Integration for Project Constellation, 2004) and NextGen (NextGen Integration and Implementation Office, 2009). Rouse (2007) summarizes the complexity of a system (or model of a system) as related to the intentions with which one addresses the systems, the characteristics of the representation that appropriately accounts for the system's boundaries, architecture, interconnections and information flows, and the multiple representations of a system.

The research work our group has conducted under funding from the NPS Acquisition Research Program, including this present report, specifically targets complexities stemming from system development risk, the interdependencies among systems, and the span-of-control of the systems or SoS managers and engineers. The objective of the research is to quantify the impact of system-specific risk and system interdependency complexities using (a) our evolving computational exploratory modeling approach and (b) an analytical Markov approach for quantifying the same effects)an investment portfolio framework for facilitating acquisition decisions. The work documented in this report comprises new improvements to an analytical component of the CEM previously introduced in prior Acquisition Research Program Symposia (Mane & DeLaurentis, 2009, 2010). The aim of the CEM is to provide decision-makers with insights into the development process by propagating development risk in the SoS network and capturing the impact that system risk, system interdependencies, and system characteristics have on the timely completion of a program. We also introduce extended work related to the Markov approach to treat the same complexities via computations on conditional probabilities that relate to the transmission of risk in network dependent systems. Furthermore, an investment portfolio-based approach complements the Markov approach with a decision tool framework as a means of leveraging performance against risk and cost.

Markov Analytical Approach

Additional complexity in the model, carefully selected, will likely increase the efficacy of the CEM. However, as a simulation-based approach, it too has limitations. Therefore, in conjunction with the further development of the CEM, the researchers are also developing an analytical approach that captures the characteristics of a network that results from the developmental interdependencies of systems. This Markov analytic approach uses a network-level metric to treat the same complexities via computations on conditional probabilities that relate to the transmission of risk in networks of interdependent systems. The Markov approach provides means to compare networks in their ability to arrest the propagation of delays caused by random disturbances and can be used as a figure of merit when designing SoS architectures that aim to achieve some desired capability.

While typical networks like the World Wide Web, social networks, and communication networks are a result of evolution, the networks created by the development of interdependent systems can be designed to achieve a desired performance. Being able to quantify the performance of such networks enables comparison of networks and, ultimately, the design of networks that optimize that performance. During development, the ability of a network of systems to propagate or arrest disruptions can be an important performance parameter when selecting a family of systems to provide a certain level of capability.

Network analysis tools can help to describe the properties of a network and to identify critical component systems. The number of links and nodes in a network, for instance, can indicate the complexity of a network by measuring the number of systems and their link. Similarly, network average degree, which describes the average number of links of each node, can indicate the level of connectivity in a network and help identify critical systems. These traditional network measures, however, are unable to describe the performance of the entire network and, consequently, comparison of networks in their ability to arrest the propagation of disruptions that can create development delays.

Delay propagation modeling is common in the airline industry, where delays at one airport can easily propagate in the aviation network and impact dependent airports. Approaches for modeling and estimating these delays, however, center on regression analysis (Xu et al., 2005; AhmadBeygi et al., 2008). AhmadBeygi et al. (2008), for instance, investigates the relationship between the potential propagation of flight delays to subsequent flights and the utilization levels of air service providers. Even though the delays can propagate indefinitely, the delay propagation structure is acyclic. A delay caused by mechanical problems to an aircraft will always propagate forward. In the system development process, delays can be cyclic, which increases the complexity of the problem and limits the ability of current approaches to quantify the total delay.

This research presents a network-level metric that captures the characteristics of a network that results from the development interdependencies of systems and provides means to compare networks in their ability to arrest the propagation of delays caused by random disturbances. As previously stated, we present, in this paper, an approach that aggregates the system and system interdependency characteristics of a development network of systems into a single metric—expectation and standard deviation of delays or costs—and enables a meaningful comparison of alternate networks in their ability to arrest the propagation of developmental delays.

The Markov approach characterizes the propagation of delays in a network of systems as a Markov Process. A Markov chain is an indexed collection of random variables used to model a sequence of dependent events such that the probability of the occurrence of a given event is solely dependent on the previous event (Sheskin, 2011). While the mathematics are well developed, we propose the application of the classical lost-miner problem (or gambler-ruin problem; Ross, 2007) to the development of a network-level metric that enables comparison of networks. The metric measures the ability of a network to arrest the propagation of delays in terms of the expected total delay and the standard deviation. The values associated with this metric captures the cascading effects of delay transmissions through transition probabilities.

The delay propagation is modeled as a Markov chain, where the states are defined as the constituent systems and the transition probabilities as the dependency strengths between systems. Of relevance is the computation of the probability of the passage in *n* time steps from any of the states to an absorbing state—a state from which one cannot exit. is the computation of this probability is analogous to a disruption due to delays being arrested after *n* time steps or the disruption being arrested after a cost of *n* dollars. Consider the development of a generalized three-system network of interdependent systems (see Figure 1). Development of system-1 (denoted by x_1) depends on the development of system-3 (x_3), and vice-versa, while development of system-2 (x_2) depends on the development of system-1. The interconnectivity between systems implies that information or design decisions in one system impact the development of a dependent system.

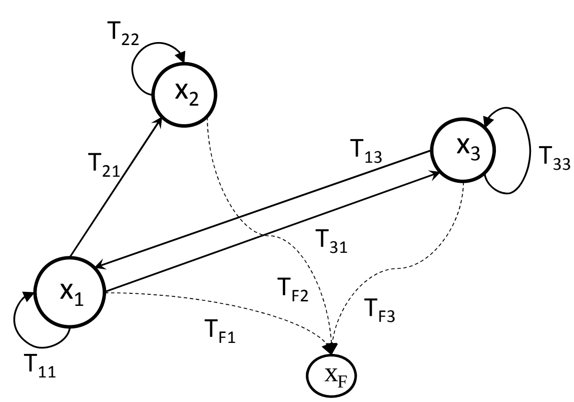

Figure 1. A Three-System Development Network

Assume that the network is modeled by an interdependency matrix T. The entries of T are positive and correspond to the conditional probability of a delay propagating to system j, given that it is in system i, $T_{ji} = P\left(x_j \mid x_i\right)$. Note that T is not necessarily symmetric. Modeling this network as a Markov chain implies that the columns of T must sum to a value less than or equal to one. In the implementation of the PageRank® algorithm, a damping d with a value between [0,1) is used to ensure that (I-dT) is invertible. Motivated by PageRank®, let state x_F represent an absorbing state and $c = T_{Fi} = P(x_F \mid x_i)$ represent the probability of a delay transitioning from a state x_i to state x_F and arresting the propagation of a delay. Note that c is defined as a row vector. This is essentially the damping term d in the PageRank® algorithm, and the transition probability matrix T can thus be defined as

$$\mathrm{T} = \begin{bmatrix} A & 0 \\ c & I \end{bmatrix} \tag{1}$$

where the matrix A, defined as

$$A_{ki} = P\left(x_k\left(n+1\right) \mid x_i\left(n\right)\right), \tag{2}$$

represents the transition probabilities of a delay being in state x_k at time $n+1$, given that there was a delay in x_i at time n. The entries of A contain all the transition probabilities of T except the transitions to the absorbing state x_F. In particular, (I-A) is invertible and the eigenvalues of A are contained in the unit disc.

To compute the location of the delays at any given time n, let

$$\xi(n) = P\left(x_j\left(n\right)\right) \tag{3}$$

be the probability of delay at location x_j at time n and let

$$b_j = P(x_j(0)) \tag{4}$$

be the vector indicating the probability that the initial delay occurs in system x_j at time n=0. Note that a delay can occur only in one system at any given time; therefore, $\sum_j b_j = 1$. This quantity can be described as the likelihood of a system to experience a delay. Additionally, let

$$c_i = P(x_F(n+1) \mid x_i(n)) \tag{5}$$

be the row vector indicating the probability of a delay being arrested at time n+1, given that it is in state x_i at time n. So the state space form of the probability of the location of delays at any given time is

$$\begin{gathered} \xi(n+1) = A\xi(n) \text{ subject to } \xi(0) = b \\ F(n \mid x_j(0)) = c\xi(n) \end{gathered} \tag{6}$$

where F is the probability of a delay transitioning to the absorbing state (e.g., the probability of a delay being arrested), given that it starts at any location x_j (see Equation 7).

$$F(n \mid x_j(0)) = P(x_F(n) \mid x_j(0)) \tag{7}$$

The probability of delays being arrested at time n can thus be expressed as

$$F(n \mid x_j(0)) = P(x_F(n) \mid x_j(0)) = cA^n b \,. \tag{8}$$

The developed set of Equations 1-8 is the implementation of a modified PageRank® algorithm that can be employed to rank the vulnerability or criticality of the constituent systems in a network of systems. As previously mentioned, system or product development can be disrupted by endogenous and/or exogenous factors that can result in development delays. Due to the network structure of the development process and system-specific characteristics, delays in one system can result in disruptions to dependent systems, which can result in further delays and the propagation of these to adjacent systems. The parameters described here provide a quantitative representation of these characteristics. The probability of the initial occurrence of a delay, $b_j = P(x_j(0))$, can be seen as a descriptor of the risk associated with the development of a system *j*. For instance, if the design of system *j* involves the development of new technologies with a low Technology Readiness Level (TRL), the probability of disruptions occurring during its development (i.e., technology setbacks, failure to meet milestones or gate reviews) is expected to be high. Conversely, if the design of system *j* is based on mature technology or off-the-shelf-parts, the likelihood of disruptions during its development process can be expected to be low. In the method presented for the Markov analytical approach, these probabilities are normalized so that $\sum_j b_j = 1$. The conditional probability of the arrest of a delay, $P(x_F(n+1) \mid x_i(n))$, can be interpreted as the ability of a system to absorb delays (e.g., a delay in upstream systems does not disrupt the development process of the system of interest) and not propagate them to dependent systems; the disruption can be a function of the size of the development program, its funding, its schedule slack, or other technological or political attributes. For instance, an underfunded, highly visible, and controversial program may be less likely to absorb delays and more likely to pass those to dependent systems, disrupting their development and causing additional delays. Alternatively, a well-funded program may be more likely to absorb delays and not propagate them to dependent systems by hiring additional personnel, acquiring more resources, or any other response that could be achieved by increasing expenditures. The transition probabilities in matrix A can be seen as descriptors of the dependency strength between systems. We assume that methods similar to the ones proposed by Sosa et al.(2003) and Sharman and Yassine (2004) can be used to quantify dependency strengths between systems based on spatial, structural, energy, material, and information interactions. The goal of this work is not to quantify these factors but to provide a means to aggregate these descriptors to compute a network-level metric that facilitates comparison of design alternatives while considering both the direct and indirect impacts of interactions between systems.

Impact of Disruptions

While the likelihood of delay propagation can help to describe the performance of a network, not all disruptions are equally important. The development risk of a network of systems can be high because of the large likelihood of disruptions (due to development delays) but also because of the impact of those disruptions. In this section, we present an extension to the proposed method that enables the quantification of risk in terms of development delay, which is well correlated with cost. Consider the same three-system network in Figure 2, but now assume that we can quantify the impact of disruptions between any two systems.

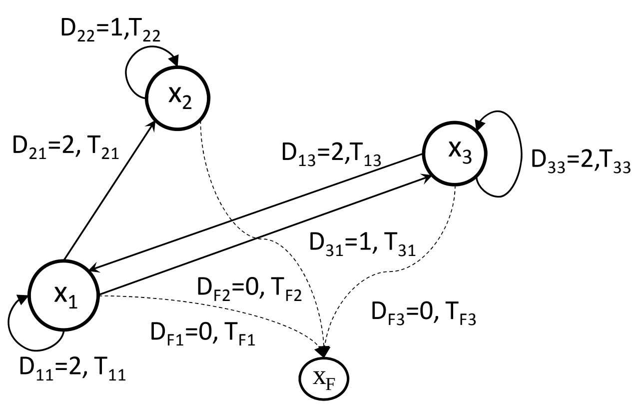

Figure 2. Three-System Development Network with Disruption Impact

The matrix D_{ji} is defined as the time delay caused by a disruption in system i, which causes a delay and a resulting disruption to system j. For example, system-1 may experience a budget cut, with some probability $P(x_1(0))$, that disrupts its development schedule. Four possibilities of disruption outcomes emerge: (1) the disruption can have no impact in the development of system-1 with probability $T_{F1} = P(x_F \mid x_1)$, and nothing is affected; (2) the disruption can cause a development delay of D_{11}= 2 time units with probability $T_{11} = P(x_1 \mid x_1)$ in the development of system-1 that is not sufficiently large enough to impact dependent systems; (3) the disruption can result in a delay of D_{31} =1 time unit with probability $T_{31} = P(x_3 \mid x_1)$ that impacts the development of system-3; or (4) the disruption can result in a delay of D_{21} = 2 time units with probability $T_{21} = P(x_2 \mid x_1)$ that impacts the development of system-2. Depending on the affected system and the likelihood of the delay propagating to additional systems, this process will continue until state x_F is reached and the propagation of the delay is arrested.

To determine the probability of a delay being arrested at time *n*, the definition of the states in the Markov approach is modified such that each transition corresponds to the accumulation of one time unit of delay, while ensuring that the transition probability matrix A retains its Markov properties and (I-A) is invertible. When the duration of the delay caused by a disruption is larger than one time unit, additional states are created to represent the one-step transition from one state to the next. Figure 3 presents a numerical example of this transformation for the three-system network.

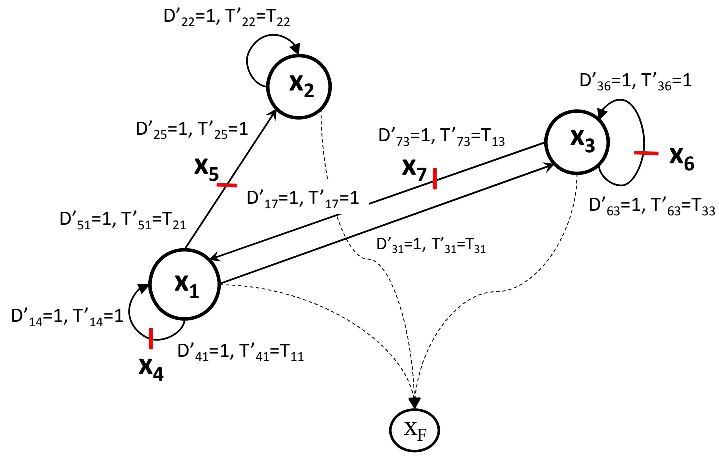

Figure 3. Re-Definition of States for Three-System Development Network

For instance, because D_{21} is of two time units, state x_5 is created so that we now have D'_{51} and D'_{25}, each of duration one time unit. Additionally, the transition probabilities are modified to accommodate this change in syntax. For instance, the probability of transitioning from state x_1 to state x_2 (T_{21}) is now represented by the probability of transitioning from state x_1 to state x_5 ($T'_{51} = P(x_5 \mid x_1) = T_{21}$) and then from state x_5 to state x_2 ($T'_{25} = P(x_2 \mid x_5) = 1$). The number of states in the modified problem can be computed as

$$S = \left[\sum_{i=1}^{J} \left(\sum_{j=1}^{J} \delta_{ji} D_{ji} - \delta_{ji} \right) \right] + J \tag{9}$$

where δ_{ij} is defined as

$$\delta_{ji} = \begin{cases} 1 \;\; if \;\; D_{ji} > 1 \;\; \forall i, j \in J \\ 0 \;\; if \;\; D_{ji} = 1 \;\; \forall i, j \in J \end{cases} \tag{10}$$

and J is the number of the states (or systems) in the original problem. Now the definition of the probability of the delay being arrested at time n can be computed using the definition in Equation 8, where $j \in S$. Note that this approach requires that the impact of disruptions be positive and represented as integer values.

Expected Delay and Standard Deviation

Computation of the conditional probability of delay arrest at time n, given that a disruption (due to a delay) starts in a given system j, provides the basis for ranking systems in a network based on their vulnerability and critically to the network by considering the direct and indirect impacts of disruptions. The posed questions are as follows: What is the expected time until a delay is arrested? What is the standard deviation? Answers to these questions provide a means to compare the criticality or performance of individual systems in a network as well as a network-level metric that describes the entire network in its ability to arrest the propagation of delays. The expectation of delay time provides a single-value metric while the standard deviation provides a means to quantify the risk associated with a given expectation.

The expected total delay, given that a disruption starts in system j, is computed as

$$\begin{aligned} E\left(F \mid x_j(0)\right) &= \sum_{n=0}^{\infty} nP\left(x_F(n) \mid x_j(0)\right) \\ &= \sum_{n=1}^{\infty} ncA^n b = cA\left(I - A\right)^{-2} \end{aligned} \tag{11}$$

while the variance is defined as

$$V = E\left(F^2 \mid x_j(0)\right) - \left(E\left(F \mid x_j(0)\right)\right)^2 \tag{12}$$

where

$$\begin{aligned} E\left(F^2 \mid x_j(0)\right) &= \sum_{n=0}^{\infty} n^2 P\left(x_F(n) \mid x_j(0)\right) \\ &= \sum_{n=1}^{\infty} n^2 cA^n b = cA\left(I + A\right)\left(I - A\right)^{-3} b \end{aligned} \tag{13}$$

Thus, the standard deviation is computed as

$$\sigma = \sqrt{V} = \sqrt{cA(I+A)(I-A)^{-3}b - \left(cA(I-A)^{-2}b\right)^2} \tag{14}$$

The mean and standard deviation computation yields values for each system in the network. Comparison of these values with each other provides a means to compare the performance of each system in the network. Therefore, one can identify the most critical or vulnerable system in the network by ranking the mean and/or standard deviation. This is essentially the same approach used by the PageRank® algorithm to rank the importance, or relevance, of web pages. While the PageRank® algorithm uses the transition probabilities to weigh the importance of links, the approach presented here uses both the transition probabilities as well as the impact of a transition. Thus, the criticality of a system is measured by both the likelihood of propagating a delay resulting from a disruption event as well as the quantified impact of the delay when the indirect, propagated consequences are captured. This provides a richer understanding of interdependent systems that can aid system engineers and designers of complex systems in the tasks of identifying critical component systems and estimating the potential schedule and cost overruns of a given system development program

The ultimate goal of the research, however, is to be able to compare the performance of entire networks. While in networks like the World Wide Web, this question may not be relevant, in the development of networks of systems, the designer has the option to design the network. Hence, a metric that enables comparison of alternatives can be quite powerful. The metric we present in this section is the total expected time and standard deviation of arresting a delay. This metric is the weighted sum of the conditional expectation of the delay time, given that a disruption starts in system *j*:

$$E(F) = \sum_{j=1}^{J} E\left(F \mid x_j(0)\right) P\left(x_j(0)\right)$$
$$= \sum_{j=1}^{J} \left[\left(cA(I-A)^{-2} b\right) P\left(x_j(0)\right)\right] \tag{15}$$

Similarly, the standard deviation for the entire network is defined as

$$\begin{aligned}
\sigma = \sqrt{V} &= \sqrt{E\left(F^2\right) - \left(E(F)\right)^2} \\
&= \sqrt{\sum_{j=1}^{S} E\left(F^2 \mid x_j(0)\right) P\left(x_j(0)\right) - \left(\sum_{j=1}^{S} \left(cA(I-A)^{-2} b\right) P\left(x_j(0)\right)\right)^2} \\
&= \sqrt{\sum_{j=1}^{S} \left(cA(I+A)(I-A)^{-3} b\right) P\left(x_j(0)\right) - \left(\sum_{j=1}^{S} \left(cA(I-A)^{-2} b\right) P\left(x_j(0)\right)\right)^2}
\end{aligned} \tag{16}$$

Utilization of this method to analyze large problems (e.g., an increased number of systems and interdependencies) hinges on the ability to quantify the transition probabilities. As the system to be analyzed grows—with more subsystems and more dependencies—the amount of information required to describe the transition probability matrix can be as low as the number of subsystems (e.g., no interdependencies) or on the order of the number of subsystems squared (e.g., all subsystems depend on all subsystems). But once the probabilities are defined, a solution to the problem becomes a matter of inverting a matrix, whose computational complexity is O(n^3) for a fully populated matrix, using Gauss-Jordan elimination (Dekker & Hoffmann, 1989); therefore, computationally, solving the matrix inverse problem is the most "expensive" aspect of the proposed method. However, if the transition probability matrix is sparse and taking advantage of the fact that its eigenvalues are smaller than one, a person could solve the matrix inversion problem via expansion by $(I-A)^{-1} = \sum_{k=0}^{\infty} A^k$.

Time-Dependent Delay Propagation

The approach presented so far assumes constant transition probabilities. The probabilities of delay propagation, however, may vary with time. As the design maturity of systems increases, development risk may decrease or increase along with changes in the interdependency strength between systems. Similarly, budget and schedule perturbations may cause changes in the probability of delay propagation in the later stages of a program that are quite different from the ones at the beginning of a program. Therefore, it would be useful to be able to describe and compare networks as interdependency characteristics change.

The proposed Markov approach can be easily extended to compute both the probability of delay arrest and the expected total delay and standard deviation as a function of changing interdependency characteristics. The state-space definition now becomes

$$\begin{aligned} \xi(n+1) &= A(n)\xi(n) \text{ subject to } \xi(0) = b \\ F(n \mid x_j(0)) &= c(n)\xi(n) \end{aligned} \quad (17)$$

The transition probability matrix A and probabilities of delay arrest for each system, *c*, are now a function of time *n* and the probability of the delay propagation being arrested after a total delay of *n* time units is

$$F(n \mid x_j(0)) = P(x_F(n) \mid x_j(0)) = c(n)\prod_{t=1}^{n} A(t)b \quad (18)$$

From this formulation, the expected delay, total delay time and standard deviation caused by a disruption due to a delay in an upstream system given that it starts in system x_j,, can be computed. The difficulty in implementing this time-dependent evaluation of the performance of a network lies in quantifying the various parameters—transition probabilities, probabilities of disruption occurrence due to delays, and the conditional probabilities of delay propagation arrest—as a function of time. One possible approach would be to use gate-reviews as discrete events that mark the changes in risk level of a given program. Additionally, one might estimate probability of initial development delay and disruption occurrence as a function of TRLs, perhaps as a function of time.

Comparison of Alternatives

There may be many different system design configurations that achieve the same capability-level. However, each configuration represents a different network comprised of different subsystems, different interdependencies, and different interdependency strengths. Among all these alternatives, which option minimizes the risk from disruptions that can result in delays? For illustration purposes, we present an example application of the proposed Markov approach to compare networks based on a preliminary case study by Asikoglu and Simpson (2010).

Asikoglu and Simpson (2010) consider a number of electro-mechanical household appliances to present their electric circuit analogy method, by which they are able to rank the components of a product based on their vulnerability to design changes. We use their example since it provides a basis for comparison of the proposed method. In their coffee maker application, they identify its 16 components, develop a Design Structure Matrix (DSM), and quantify the interdependency strengths between components by using the Module Complexity Score (MCS) of component interfaces to develop a weighted-MCS that they employ in the electric circuit analysis.

We consider the same problem and pose it in the context of development time. We assume that the development of the coffee maker is divided between different design teams that are dependent on each other for the development of the coffee maker. We interpret the interdependency weights between the coffee maker components defined by Asikoglu and Simpson (2010) in the weighted-MCS as the interdependency strengths that indicate the relative difference in the likelihood of each component propagating its delays to dependent components. We use the weighted-MCS matrix to compute the transition probability matrix T_{ij} by normalizing the entire matrix by the sum of its entries. By this process, we are using the data gathered and analyzed by Asikoglu and Simpson as an indicator of the relative likelihood of delay transmission between systems. Components that are connected by multiple types of interfaces and have more interfaces will have a higher probability of transmitting delays to dependent systems. This is a reasonable assumption because tighter coupling between components increases the likelihood of disruptions in one component having an impact on dependent components.

Furthermore, we assume that the disruption impact is of one time unit for all interdependencies (e.g., D_{ji} has entries of one), that all components are equally likely to arrest the propagation of a delay with probability 0.1 (e.g., T_{Fi} = 0.1), and that all components are equally likely to experience an initial disruption that results in a delay (e.g., $P(x_i(0)) = 1/J = 1/16$). Note that because the electric circuit analogy does not include all these attributes, a comparison of the performance of the two methods (electric circuit analogy versus the approach proposed in this section) is not expected to be identical. Having generated T_{ji} and D_{ji}, we can easily compute the expected delay and standard deviation for this coffee maker network of components and identify the (direct and indirect) vulnerability to developmental disruptions via network-level metric. Table 1 presents these results along with a comparison against the change-resistance (CR) and the weighted-MCS results presented by Asikoglu and Simpson (2010).

Table 1. Component Criticality Ranking and Comparison

Component	Change Resistance Ranking[**Error! Bookmark not defined.**]	Weighted-MCS Ranking [**Error! Bookmark not defined.**]	Our Approach Ranking	Our Approach [Exp, Std Dev]
Component-1	9	8	8	[0.0030, 0.0597]
Component-2	6	5	5	[0.0044, 0.0716]
Component-3	12	11	11	[0.0010, 0.0324]
Component-4	16	15	15	[0.0002, 0.0131]
Component-5	13	12	12	[0.0010, 0.0321]
Component-6	11	10	10	[0.0013, 0.0387]
Component-7	7	14	14	[0.0003, 0.0190]
Component-8	1	1	2	[0.0139, 0.1326]
Component-9	3	3	3	[0.0085, 0.1079]
Component-10	4	4	4	[0.0073, 0.0992]
Component-11	2	2	1	[0.0141, 0.1367]
Component-12	8	6	6	[0.0036, 0.0676]
Component-13	10	9	9	[0.0016, 0.0416]
Component-14	14	13	13	[0.0005, 0.0221]
Component-15	15	16	16	[0.0002, 0.0127]
Component-16	5	7	7	[0.0035, 0.0681]
Total				[0.0040, 0.2806]

Concerning which components are most vulnerable, our method reaches similar conclusions to the two approaches presented by Asikoglu and Simpson (2010). The ranking values presented in Table 1 indicate which components contribute most to the expected total delay and, hence, are the most critical components in the coffee maker. The coffee maker example assumes that all interdependencies are undirected (e.g., the weighted-MCS matrix is symmetric). While this may be true for the coffee maker example, other systems may have directed dependencies or dependencies that have asymmetrical magnitudes. For instance, the design of the housing in a coffee maker may impact the design of the carafe more than the design of the carafe may impact the design of the housing. Our approach can model this type of interdependency as well as provide a network-level metric—in terms of expectation and standard deviation—that evaluates the entire network in its resilience to delay propagation. This modeling of network interdependencies can be useful if one is interested in the direct comparison of two or more designs.

To demonstrate this network-comparison ability, we consider an alternate coffee maker that has only eight components (e.g., $J = 8$) and which has a combination of directed and undirected dependencies, and wish to compare the performance of the two designs. The components of this design are presented in this section as groupings of the components in the original coffee maker. We construct the weighted-MCS matrix by combining the values of the original 16-component weighted-MCS matrix and use this asymmetric network to generate the transition probability matrix by normalizing the entries of the modified weighted-MCS matrix by the sum of it entries. The normalization of entries results in the probability matrix presented in Table 2. For instance, the probability of a delay in the development of Component-6,8,12 transitioning (propagating) to Component-11 and causing a disruption is 0.2235, while the probability of a delay in the development of Component-11 propagating to Component-6,8,12 is 0.0930.

Table 2. Transition Probability Matrix for Alternate Coffee Maker Design

$P(T_{ji})$	Component-1	Component-3,4	Component-6,8,12	Component-13	Component-11	Component-15	Component-10	Component-9
Component-1	-	0.131	0.0902	0.0074			0.0301	0.0065
Component-3,4	0.0131	-						
Component-6,8,12	0.0902		-		0.0930		0.0372	
Component-13	0.0065			-		0.0065		
Component-11			0.2235		-			
Component-15				0.0065		-		
Component-10	0.0301		0.0800				-	0.0800
Component-9	0.0065						0.0080	-

Furthermore, we assume that all eight components are equally likely to experience a disruption (e.g., $P(x_i(0)) = 1/J = 1/8$). The question we pose is, which architecture is best in the context of development time if the alternate coffee maker design has the dependency characteristics of Table 2 (e.g., expected delays and standard deviation due to development disruptions caused by the occurrence and propagation of delays)? Table 3 presents the expectation and standard deviation of the total delay time for the alternate coffee maker along with a ranking of the importance of each component.

Table 3. Performance of Alternate Coffee Maker Design

Component	Alternate Coffee Maker [Exp, Std Dev]	Ranking
Component-1	[0.0224, 0.1783]	4
Component-3,4	[0.0019, 0.0513]	6
Component-6,8,12	[0.0339, 0.2203]	2
Component-13	[0.0018, 0.0463]	7
Component-11	[0.0355, 0.2301]	1
Component-15	[0.0008, 0.0292]	8
Component-10	[0.0282, 0.1957]	3
Component-9	[0.0132, 0.1370]	5
Total	[0.0172, 0.4427]	

The total expected delay of this alternate design is 0.0172, higher than the total expected delay of the original coffee maker. This value of expected delay indicates that, for the assumed transition probabilities, the original coffee maker design outperforms the alternate design, even though the latter contains half the number of components. Therefore, the interdependency characteristics of this seemingly less complex product make it a less desirable design from a development perspective. Furthermore, the standard deviation adds to this poor performance, indicating a higher risk and less certainty in the expected performance when faced with developmental disruptions due to delays.

Although a simple example, this network comparison brings forth the difficulties and lack of intuition in quantifying complexities of interdependent systems. While the method relies on the estimation of several parameters, it does provide a means to quantitatively compare networks of interdependent systems.

Investment Portfolio Approach

A key component of our proposed research under this project was the development of an ability to balance capability and risk in acquiring systems in an SoS context. Research work accomplished in this phase and described in this report section centers on an investment decision-making tool that provides a means of balancing capability development against cost and interdependent risks through the use of Modern Portfolio Theory (MPT). Prior works from surveyed literature have seen the successful use of portfolio management techniques to address strategic level asset acquisition and are extendable to include multi-period considerations. *Real options analysis*, for example, has been shown to be effective and is widely used across various industries to evaluate discrete, long-term investment strategies. Komoroski (2006), for example, has developed a methodology that addressees strategic financial decisions through an eight-phase process using a toolbox of financial techniques—including portfolio optimization techniques. These frameworks are geared toward financial uncertainty considerations of strategic projects and do not explicitly address technical architecture and/or evolving SoS-wide capabilities.

The investment portfolio approach this section does not attempt to replace but rather complements existing methodologies by more directly addressing issues of integration and acquisition from a *robust portfolio theory* standpoint. Robust methodologies have been widely used by financial engineering practitioners to manage portfolios in the face of market volatility and uncertainties. The developed approach in this section is also aimed at improved means of performing acquisition, integration, and development decisions while maintaining advantages in balancing systems acquisition against evolving capability requirements. The research work in this section also addresses more recent efforts in acquisition that have emphasized the implementation of open architectures and modularity to facilitate competition (to lower cost) and innovation.

Open architecture (OA) involves the design and implementation of systems that conform to a common and unified set of technical interfaces and business standards. This form of architecture results in the development of modular systems and increases opportunities for innovation and rapid development of new technologies that can be readily integrated/swapped into current architectures. The Littoral Combat Ship (LCS) platform, for example, has recognized the need for multivendor acquisitions and OA implementations to ensure greater technological adaptability. The LCS program exploits the benefits of *dual award contracting* under fixed price initiatives (FPI), along with rapid technology insertion processes and open architectures, to fulfill evolving technological and mission requirements of littoral warfare. The combination of dual contracting and system modularity helps achieve the necessary cost reductions while maintaining a greater degree of adaptability towards changing mission requirements. Although the platform is not, strictly speaking, an SoS, it nevertheless is an excellent representative microcosm of what constitutes an SoS and carries many comparable salient features.

Figure 4. Littoral Combat Ship Layout
(“LCS: The USA’s New Littoral Combat Ships,” 2011)

The benefits of open architectures and competitive contracting are intuitively clear and have been shown to generate notable cost savings as exhibited in previous development projects such as joint direct attack munitions (JDAM; GAO 2007b) . However, system integrators and program managers are often faced with the challenge of leveraging the potential benefits of introducing new and improved systems against potential developmental disruptions and cost considerations. Although the LCS program had significant success through the dual contracting scheme, it still experienced cost overruns due to a variety of problems. The problems included risks from a simultaneous design and build strategy due to schedule constraints, unrealistic budget expectations, and market risk from the greatly increased price of steel during the development period (O’Rourke, 2011). There have also been revisions in the requirements of fleet capabilities and refocusing of intended capabilities (O’Rourke, 2011).

Concept Acquisition Portfolio: Littoral Combat Ship Example

The littoral combat ships are designed and developed by two primary contractors—General Dynamics and Lockheed Martin—as a result of the Navy’s dual contract award strategy that seeks to minimize costs through competitive contracting. The ships are designed to serve as primary units in close coastal littoral warfare and take advantage of modularized onboard packages (systems) that are interchangeable for different operational requirements. These packages include the Anti-Submarine Warfare (ASW), Mine Counter Measure (MCM) and Surface warfare (SUW) packages. More recent developments have seen the introduction of an irregular warfare package for assistance and general support missions. Although the LCS is not, strictly speaking, an SoS, it nevertheless exhibits striking resemblance to one where the conglomeration of systems provide the intended overarching capabilities. The ongoing work in this demonstration assumes a representative acquisition problem using the LCS acquisition case where the objective is to achieve desired combat effectiveness and operational capabilities while minimizing cost and development risk. The simple model inputs and characteristics are described in Table 4.

Table 4. Individual System Information

		System Capabilities					System Req.		Develop. Time	Acq. Cost
		Weapon Strike Range	Threat Detection Range	Anti Mine Detection Speed	Comm. Capacity	Air/Sea State Capacity	Air/Sea State	Comm.	(Years)	($)
Package										
ASW	Variable Depth	0	50	999	0	0	0	300	3	3000000
	Multi Fcn Tow	0	40	999	0	0	0	200	2	2000000
	Lightweight tow	0	30	999	0	0	0	100	4	4000000
MCN	RAMCS II	0	0	40	0	0	3	100	1	1000000
	ALMDS (MH-60)	0	0	10	0	0	4	200	2	2000000
SUW	N-LOS Missiles	25	0	999	0	0	0	300	3	3000000
	Griffin Missiles	3	0	999	0	0	0	200	4	4000000
Seaframe	Package System 1	0	0	999	100	0	0	0	5	5000000
& Combat	Package System 2	0	0	999	200	4	0	0	4	4000000
Management	Package System 3	0	0	999	300	3	0	0	3	3000000

Table 4 is a hypothetical and simplified catalogue of individual systems available to the Navy in its pursuit of achieving desired capabilities. Although the numbers are hypothetical and do not explicitly illustrate live data, the salient features of the acquisition problem are still preserved. Table 4 lists systems that are available for each of the three mission packages—ASW, MCM, SUW—along with an individual rating of system capabilities and requirements for the systems to operate. Additionally, Table 4 provides the system development time and associated acquisition costs. Systems that are unable to provide a particular capability (or do not have a particular requirement) have a zero entry. Although the sea frame is typically a single system, the current sample problem couples the sea frame with battle management software as a base system that provides intra system capabilities. The development of these systems is based on a projected time schedule that is inherently subject to overruns and risk. This element is captured in the covariance matrix shown in Table 5.

Table 5. System Interdependency and Development Risk (Covariance)

	Variable Depth	Multi Fcn Tow	Lightweight tow	RAMCS II	ALMDS (MH-60)	N-LOS Missiles	Griffin Missiles	Package System 1	Package System 2	Package System 3
Variable Depth	0.1	0	0	0	0	0	0	0	0	0
Multi Fcn Tow	0	0.6	0	0	0	0	0	0	0.1	0
Lightweight tow	0	0	0.2	0	0	0	0	0	0	0.2
RAMCS II	0	0	0	0.3	0.1	0	0	0	0.2	0
ALMDS (MH-60)	0	0	0	1	0.1	0	0	0	0	0.3
N-LOS Missiles	0	0	0	0	0	0.5	0.2	0	0.1	0
Griffin Missiles	0	0	0	0	0	0.2	0.3	0	0	0
Package System 1	0	0	0	0	0	0	0	0.5	0	0
Package System 2	0	0.1	0	0.2	0	0.1	0	0	0.3	0
Package System 3	0	0	0.2	0	0.3	0	0	0	0	0.2

Table 5 shows the risk and interdependency aspects of the decision process. The diagonal terms represent the variance (degree of deviation from expected time) in development time. The off-diagonal terms are the variances due to interdependencies between individual systems that have commonly developed subsystems. For example, since the N-LOS and Griffin missile systems are both developed by Northrop Grumman, it is conceivable that they have common parts or undergo similar processes in development and manufacturing. The covariance value in the cross term therefore represents joint development risk for the two systems.

Estimation of these quantities can come directly from manufacturing and development data. In the case of new systems, the quantities can be estimated heuristically using basic rules similar to those used in project management techniques such as PERT and other CPM methods. The entries of the matrix in Table 5 are typically inferred from data; in this case, the values are hypothetically developed for the concept example problem. Most of the individual systems do not bear many interdependencies, with the exception of the sea frame and combat management support systems that are interlinked more explicitly to other listed systems in Table 5..

Investment Model Formulation and Solution

The problem statement for the given acquisition problem is formulated as a mathematical optimization problem, which requires the definition of two primary segments. The *objective function* is the equation that describes the primary metric to be optimized. This typically translates to, for example, the maximization of profits or minimization of costs/risk in the commercial sense. The second important aspect deals with the formulation of *constraints*, which are equations that typically describe resource (e.g., time, cost) constraints on the system and can be manipulated to reflect the salient conditions of the problem to be solved. The investment portfolio problem presented in the formulation shown below seeks to maximize the aggregate capabilities of an SoS architecture while minimizing cost, developmental time, and integration risks. The mathematical model for the concept problem can be written as the following:

$$\max\left(\sum_q\left(\frac{S_{qc}-R_c}{R_c}\cdot w\cdot X_q^B\right)-\lambda\left(X_q^F\right)^T\Sigma_{ij}X_q^F-\sum_q\left(C_qX_q^B\right)\right) \tag{19}$$

$$X_q^F=\frac{X_q^BC_q}{B}\text{(Portfolio Fractions)} \tag{20}$$

$$\sum_q C_qX_q^B+\varepsilon=\text{B (Budget Constraint)} \tag{21}$$

$$\sum_q S_{qC}X_q^B\geq\sum_q S_{qR}X_q^B\ \text{(Satisfy All System Requirements)} \tag{22}$$

$$X_1^B+X_1^B+X_1^B=1\ \text{(ASW System Compatibility)} \tag{23}$$

$$X_4^B+X_5^B=1\ \text{(MCM System Compatibility)} \tag{24}$$

$$X_6^B + X_7^B = 1 \text{ (SUW System Compatibility)} \tag{25}$$

$$X_8^B + X_9^B + X_{10}^B = 1 \text{ (Package System Compatibility)} \tag{26}$$

$$X_q^B \in \{0,1\} \text{(binary)} \tag{27}$$

The mathematical model shown by Equations 19–27 represents the formulation of a traditional single-stage optimization problem that is typical of operations research and financial engineering circles. The current form for the portfolio model at hand is known as a quadratic integer program (QIP) and is based on the Markowitz formulation that seeks to generate optimal portfolios that balance potential expected rewards against risk. Equation 19 is the *objective function*—in this equation, the objective is to maximize overall capability while minimizing cost and development risk. Equation 20 is the fraction of the budget invested in individual systems. Equation 21 is the budgeting constraints, where the sum of all investments in individual systems (and savings) must be equal to the total budget allotted. Equation 22 ensures that all requirements of individual systems must be met. Equations 23–26 are the individual system compatibilities. In Equations 23–26, this translates to the selection of one system from each mission package (ASW, MCM, SUW) and a seaframe and combat management package that services the mission modules. These packages are mutually exclusive and therefore warrant a total selection of summation equal to 1, which ensures that no two packages per category are selected to satisfy the respective requirements. The covariance matrix, as denoted by Σ_{ij}, represents variations in development time due to system interdependencies. The Σ_{ij} formulation is amenable to several methods of solution using both freeware and commercially available solvers that are written with system integration and IT considerations in mind. Models using these solver platforms are readily integrated into IT environments and enterprise systems, providing a model-centric environment for the decision-making process.

Preliminary Results

The portfolio optimization problem is modeled and solved using a commercial solver by varying the risk aversion parameter, λ , to generate the performance efficiency frontier. By changing this parameter, the portfolio's aversion to risk is increased as the penalty effect of λ is more pronounced with increasing value. The increase in the value of risk aversion forces the portfolio to select assets (systems) that are lower risk, which consequently results in a lower but less risky performance, as exhibited in Figure 5.

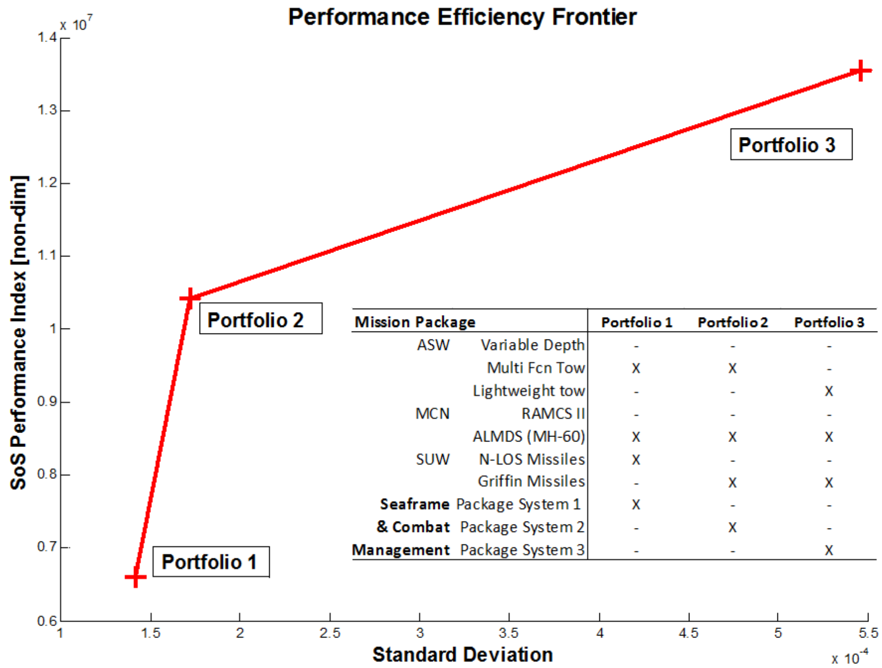

Figure 5. Portfolio Reward to Risk Ratio

Error! Reference source not found.Error! Reference source not found. shows what is known as the Markowitz efficiency frontier, where a collection of optimal portfolios that maximizes performance are shown for decreasing values of risk aversion. Each labeled portfolio point on the frontier is comprised of selected systems, as shown in the given Figure 5. In a more realistic setting, Figure 5 can be used to explore the benefits of introducing higher-performing, though potentially riskier, systems into the conglomeration. For instance, the highest-risk portfolio includes the use of the N-LOS missile system. In reality, the N-LOS system was extricated from the LCS program due to poor consistency in performance and replaced by the shorter-ranged (and cheaper) but more reliable Griffin missile system. This tradeoff of performance due to poor consistency is exhibited in Figure 5, where reduced performance is complemented by reduced risk. The results show the potential valuation of risk taken with the introduction of each system for increased performance. It also identifies critical systems that are common across the performance index, such as the Airborne Laser Mine Detection System (ALMDS) that is a fixed asset across all ranges of performance.. The results from this portfolio frontier serve as a complement to the CEM methodology; the CEM can be used to explore inherent network dynamics for each portfolio that exists on the frontier.

Future Work

Robust Portfolio Method

It is well known in financial engineering circles that the Markowitz formulation, as used in the simplified LCS scenario, is sensitive to changes in estimated quantities of the covariance matrix (system interdependencies) and expected return (system performance). The sensitivity due to poor covariance estimations can result in highly inefficient portfolios due to errors in estimation or market shifts. Such sensitivity issues has prompted the development of a variety of robust methods in portfolio analysis to ensure that the chosen portfolio of assets are stable against potential changes in market conditions/expected volatility.

The generalized version of the current portfolio formulation as dictated in Equations 19-27 can be reformulated using robust optimization techniques; this includes Semi-Definite Programming (SDP) approaches (Fabozzi et al., 2007; Tutuncu & Cornuejols, 2007) that are extensions of modern portfolio and control theory. The reformulation allows for possible changes in estimated quantities (e.g., due to market shifts in pricing, volatility, system interdependencies) are taken into consideration more explicitly as *uncertainty sets*. The resulting portfolio allocation will not change appreciably, even if salient estimated quantities or benefits change (within prescribed limits). In the context of an acquisition problem, the use of a robust formulation translates to reduced transaction costs associated with having to extricate legacy systems and robustness against market estimation errors, volatility, and changing requirement conditions. The general form of the portfolio problem in this research can be reposed as a robust, SDP problem, as given by Equation 28 (Fabozzi et al., 2007):

$$
\begin{gathered}
\max_{x}\left\{\min_{\mu\in U_{\mu}}\left\{\mu_i x\right\}-\lambda\left\{\left\langle\overline{\Lambda}\overline{\Sigma}\right\rangle-\left\langle\underline{\Lambda}\underline{\Sigma}\right\rangle\right\}\right\} \\
\text{s.t.} \\
\begin{bmatrix}\overline{\Lambda}-\underline{\Lambda} & x \\ x' & 1\end{bmatrix} \pm \mathbf{0} \\
\mathbf{Ax} \geq \mathbf{b} \\
\mathbf{Cx} = \mathbf{d} \\
\overline{\Lambda} \geq \mathbf{0}, \underline{\Lambda} \geq \mathbf{0} \\
U_{\delta}\left(\hat{\mu}\right)=\left\{\mu \mid \mu_i-\hat{\mu}_i \mid \leq \delta_i, i=1,\ldots,N\right\} \\
\underline{\Sigma} \leq \Sigma \leq \overline{\Sigma}
\end{gathered} \tag{28}
$$

Although the complexity of the optimization problem increases, it is nevertheless very amenable to a collection of numerical methods and provides good performance for realistic portfolio problems, especially under highly volatile conditions (Fabozzi et al., 2007). Equations 29 and 30 in the following section represent the uncertainty bounds of the performance (capability) of each system and the associated risk of interdependencies.

Multi-Period Investment Portfolio

The general portfolio formulation in this section considers a static portfolio approach without consideration for sequential, multi-period investment horizons. An addition of multi-step considerations into the decision process makes the problem amenable to dynamic programming and control theory methods. The extension of the investment portfolio approach generally amounts to rewriting the objective of the optimization problem as the following:

$$
\max \underbrace{\left(\sum_q\left(\frac{S_{qc}-R_c}{R_c}\cdot w\cdot X_q^B\right)-\lambda\left(X_q^F\right)^T\Sigma_{ij}X_q^F-\sum_q\left(C_qX_q^B\right)\right)}_{A}{}_{t}+E\left(A_{t+1}\mid w_{t+1},\Sigma_{t+1},\lambda_{t+1}\right) \tag{29}
$$

The objective function now reflects consequential effects where current acquisition decisions affect latter decisions, as denoted by the expectation term of Equation 29. The stochastic nature of the mathematical problem in Equation 29 is a stochastic control problem, which has a variety of efficient and industry-tested solutions, such as approximate dynamic programming (ADP) and Model Predictive Control (MPC). Thus, the current motivation of extending the established research framework is to bring these tools (such as ADP amd MPC) to bear upon the immediate acquisition problem, keeping enterprise, model-centric architectures of decision-making processes in mind.

Markov Model Extensions

The analytical Markov model will be extended to include dynamic analysis of failure modes that are associated with the Markov approach presented in this report. The extension of the Markov approach will include the framework of identifying delay time metrics at each node to the analysis of eigenmodes (connected trees/networks) of disruption sequences. The identification of disruption eigenmodes is particularly useful in model-centric enterprise systems, where clear visualization of connectivity between individual systems is crucial to the design and diagnosis of underlying problems.

Biographies of Investigators

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